



Auction House Price Analysis





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The Auction House

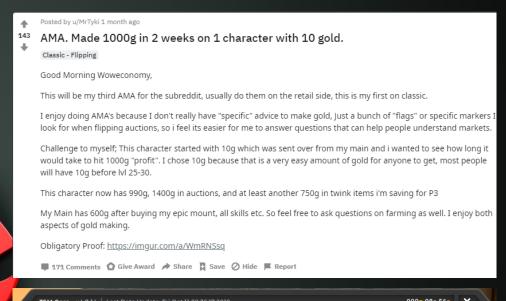
 Faction-Wide Hub for Player-To-Player Trading

- Dynamic, Highly Volatile Economy
- Player Driven Competitive Pricing
- Prices Affected by Demand/Popularity, Level, Relevance



The Auction House

- Players Exploit Behavior for Profit
- No need for collecting items in world
- Generates gold faster than any other method of income

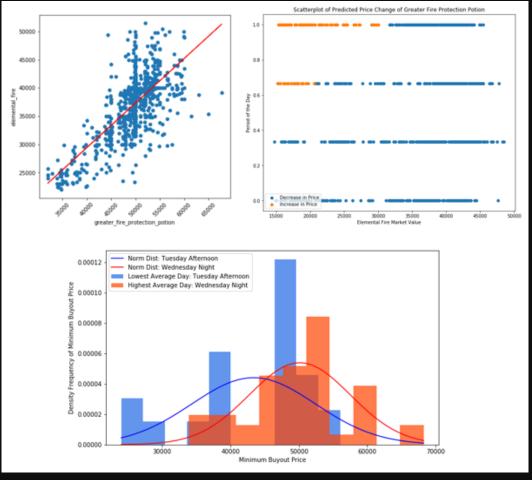




Analyzing Price Behavior

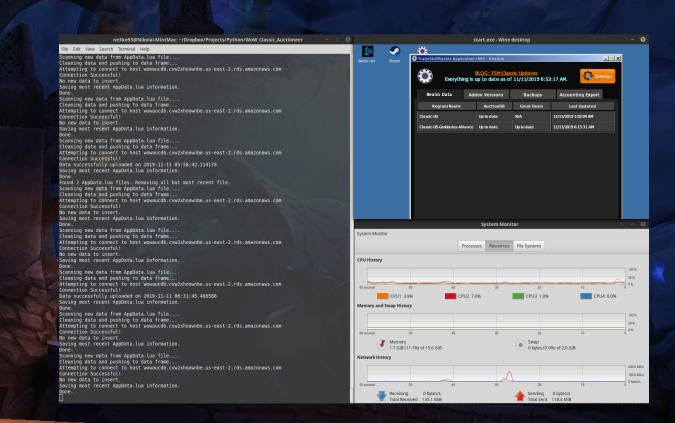
- Simple Linear Regression
 - Correlations between Craftables & Materials
- Confidence Interval Estimation
 - Difference in mean price between Time Intervals
- K-Means Clustering
 - Predicting Price Change Behavior





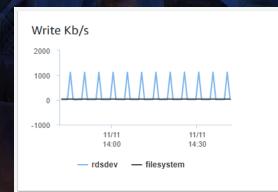
Data Collection

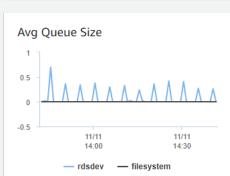
- Script perpetually running on Linux server
- Scans TradeSkillMaster data file every second – AppData.lua
- If update to file, parses and preprocesses data (JSON format)
- Pushes processed data to AWS server

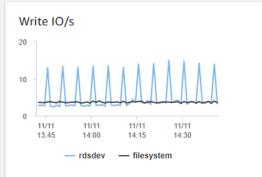


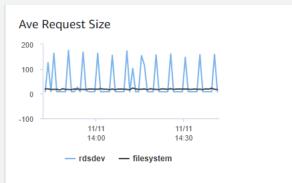
AWS Database

- 5966 Items
- ~Hourly scans dating back to October 7, 2019
- Attributes: itemid, marketvalue, minbuyout, historical, numauctions, scantime
 - Predicted variable based off minbuyout









Simple Linear Regression - Algorithm

- Inputs
 - Item ID of Craftables,
 - Item Name of Craftable
 - List of Item IDs of Materials
 - List of Names of Materials
- Output
 - Summary of Linear Correlations Ordered by Pearson Correlation Coefficient
 - Plots of Pairwise SLR Relationships

- Steps
 - Extract scantimes & minimum buyout prices for all items
 - 2. Merge Data Sets
 - Produce Pearson Correlation Coefficient Matrix
 - 1. pandas.dataframe.corr()
 - 4. Model SLR Line for each pairwise relationship
 - 1. Estimate Slope β & y-intercept α
 - 2. Calculate t-statistic
 - 3. Calculate p-value
 - 1. scipy.stats.t.cdf()
 - 4. Calculate Coefficient of Determination \mathbb{R}^2

Simple Linear Regression - Mathematics

Pearson Correlation Coefficient

$$r_{xy} = \frac{\sum_{i=1}^{n} (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{n} (x_i - \bar{x})^2} \sqrt{\sum_{i=1}^{n} (y_i - \bar{y})^2}}$$

• Slope β

$$\hat{\beta} = \frac{\sum_{i=1}^{n} (x_i - \bar{x})(y_i - \bar{y})}{\sum_{i=1}^{n} (x_i - \bar{x})^2}$$

• Y-Intercept α

$$\hat{a} = \bar{y} - \hat{\beta}\bar{a}$$

T-statistic

$$t = \frac{\hat{\beta}}{SE(\hat{\beta})}$$

Standard Error

$$SE(\hat{\beta}) = \sqrt{\frac{1}{n-2} \frac{\sum_{i=1}^{n} (y_i - \hat{y})^2}{\sum_{i=1}^{n} (x_i - \bar{x})^2}}$$

P-value

$$p = \begin{cases} 1 - \Phi(t) & \text{if } \hat{\beta} \le 0 \\ \Phi(t) & \text{if } \hat{\beta} > 0 \end{cases}$$

Coefficient of Determination

$$R^2 = 1 - \frac{SSR}{SST}$$

Residual Sum of Squares

$$SSR = \sum_{i=1}^{n} (\hat{y}_i - \bar{y})^2$$

Total Sum of Squares

$$SST = \sum_{i=1}^{n} (y_i - \bar{y})^2$$

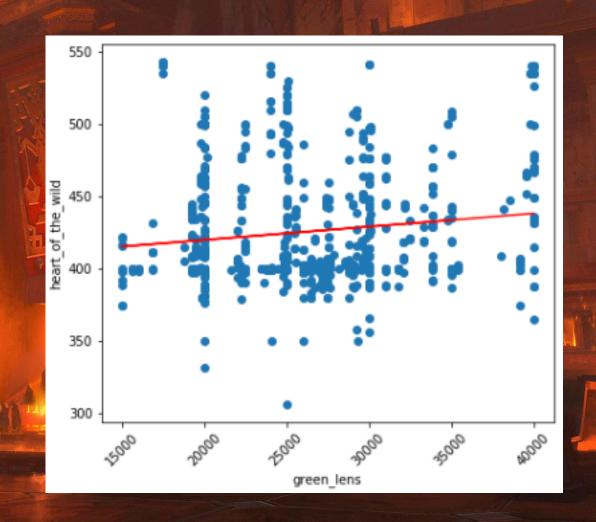
Simple Linear Regression – BiS Results

- Generally Quite Poor Performance
- Green Lens vs Heart of the Wild

•
$$p = 2.84e^{-5}$$

•
$$r_{xy} = 0.137$$

• $R^2 = 0.0188$



Simple Linear Regression – Devilsaur Leather

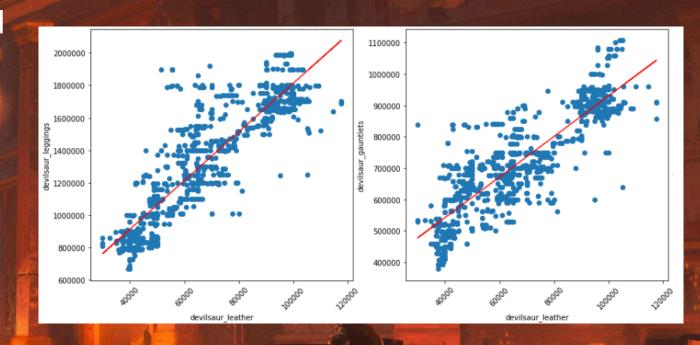
- Contrary to other BiS, performed well
- Devilsaur Leggings vs Devilsaur Leather

•
$$p = 0.00$$

•
$$r_{xy} = 0.81$$

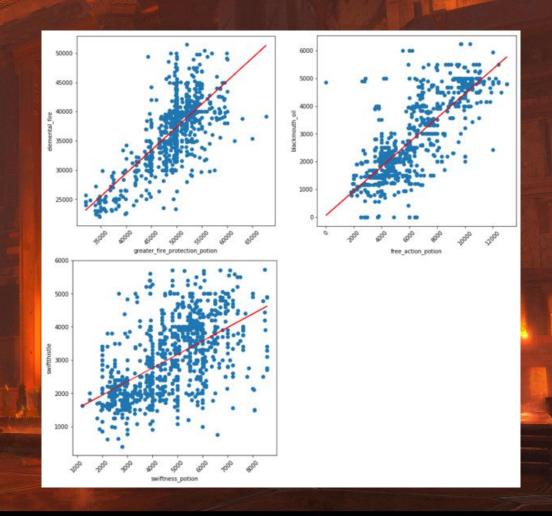
•
$$R^2 = 0.67$$

- Devilsaur Gauntlets vs Devilsaur Leather
 - p = 0.00
 - $r_{xy} = 0.828$
 - $R^2 = 0.68$



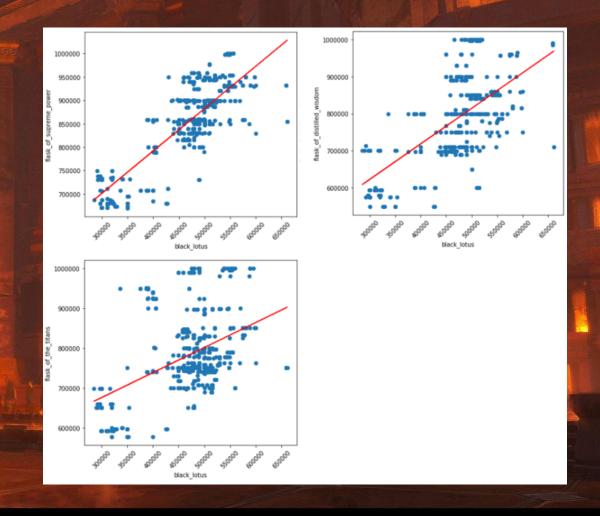
Simple Linear Regression – Consumables

- Consistently performed better than BiS
- Greater Fire Protection Potion vs Elemental Fire
 - $p = 0.00, r_{xy} = 0.72, R^2 = 0.52$
- Free Action Potion vs Blackmouth Oil
 - $p = 0.00, r_{xy} = 0.78, R^2 = 0.608$
- Swiftness Potion vs Swiftthistle
 - $p = 0.00, r_{xy} = 0.57, R^2 = 0.327$



Simple Linear Regression – Flasks

- All share same main ingredient Black Lotus
- Correlation proportional to player population
- Flask of Supreme Power vs Black Lotus
 - $p = 0.00, r_{xy} = 0.81, R^2 = 0.657$
- Flask of Distilled Wisdom vs Black Lotus
 - $p = 0.00, r_{xy} = 0.607, R^2 = 0.369$
- Flask of the Titans vs Black Lotus
 - $p = 0.00, r_{xy} = 0.431, R^2 = 0.186$



Time-Interval Analysis - Methodology

- Split minimum buyout prices into subsets based on time interval
 - Day of the Week, Hour of the Day, Part of the Day (Morning, Afternoon, Evening, Night)
- Compare Best Performing Interval and Worst Performing Interval
 - Performance measured by sample mean
- Significance measured by p-value within significance level $\alpha=0.05$

T-statistic for difference in means

$$t = \frac{\mu_1 - \mu_2}{\sqrt{\sigma_1^2/n_1} \sqrt{\sigma_2^2/n_2}}$$

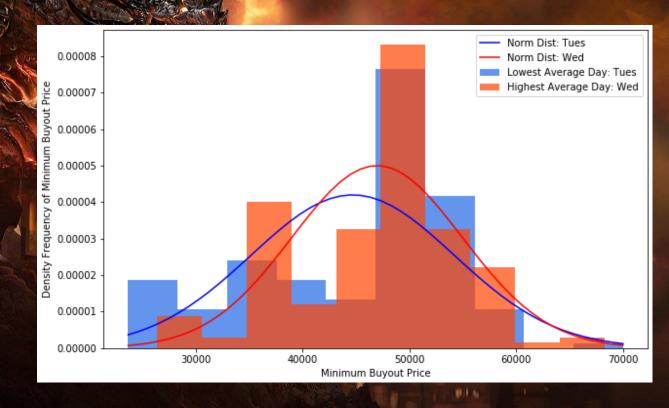
• Degrees of Freedom

$$df = \frac{\left(\frac{\sigma_1^2}{n_1} + \frac{\sigma_2^2}{n_2}\right)^2}{\left(\frac{\sigma_1^2}{n_1}\right)^2 / \left(n_1 - 1\right) + \frac{\left(\frac{\sigma_2^2}{n_2}\right)^2}{\left(n_2 - 1\right)}}$$

• p-value $p = 1 - \phi(t)$

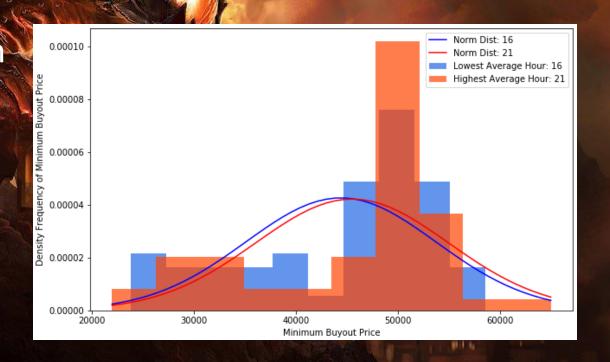
Time-Interval Analysis – Weekday Intervals

- Best Performing Day Wednesday
 - $\mu = 4g 69s 84c$, $\sigma = 79s 81c$
- Worst Performing Day Tuesday
 - $\mu = 4g \ 46s \ 94c$, $\sigma = 95s \ 06c$
- P-value: p = 0.0102



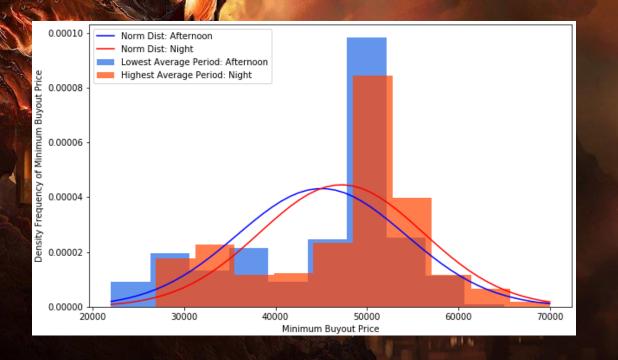
Time-Interval Analysis - Hourly Intervals

- Best Performing Hour 9pm-10pm
 - $\mu = 4g 84s 10c$, $\sigma = 88s 36c$
- Worst Performing Day Tuesday
 - $\mu = 4g \ 42s \ 76c$, $\sigma = 94s \ 46c$
- P-value: p = 0.2712



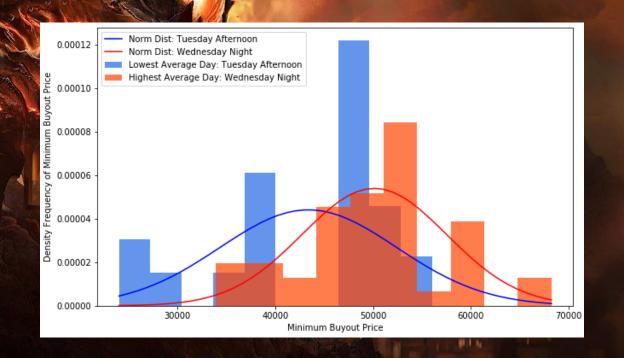
Time-Interval Analysis – Part of Day Intervals

- Best Performing PoD Night (9pm-5am)
 - $\mu = 4g 71s 98c$, $\sigma = 89s 58c$
- Worst Performing Day Afternoon (12pm-5pm)
 - $\mu = 4g \, 50s \, 17c$, $\sigma = 92s \, 44c$
- P-value: p = 0.00137



Time-Interval Analysis — Theoretical Best vs Theoretical Worst

- Wednesday Night (Theoretical Best)
 - $\mu = 5g \ 01s \ 26c$, $\sigma = 74s \ 02c$
- Tuesday Afternoon (Theoretical Worst)
 - $\mu = 4g \ 33s \ 79c$, $\sigma = 90s \ 60c$
- P-value: p = 0.000164



K-Means Clustering - Algorithm

- Input
 - Matrix of Predictor Variables
 - Real Class Values
 - K value (# of classes)
 - Stopping Condition
 - 1. Number of iterations
 - 2. Convergence of Centroids
 - Distance Metric
 - Euclidean, Manhattan, Infinite, Cosine, Lr
 - r for Lr distance

- Output
 - Matrix of Centroids for each Cluster
 - Predicted Classes
 - Accuracy of Prediction
 - Confusion Matrix

K-Means Clustering - Algorithm

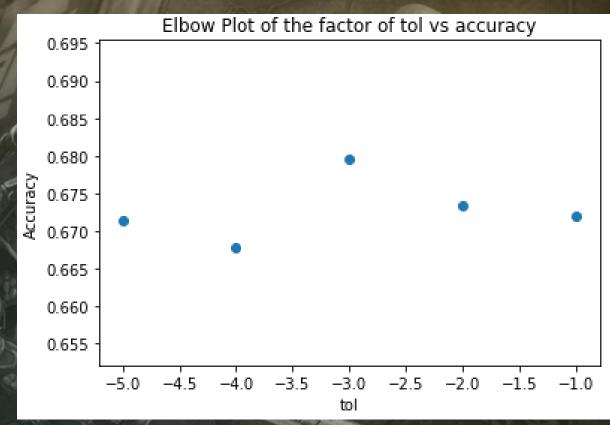
- Initialization
 - Centroids
 - First centroid picked as random point
 - Following centroids picked as furthest distance from previous centroids
 - Initial Predicted Classes Centroid of minimum distance from point

- Iteration
 - Assign class for each instance by minimum distance from centroids
 - Update centroids to be center of each new cluster
- Convergence
 - 1. Reach assigned number of iterations
 - Centroids converge to central point

K-Means Clustering - Tuning



- Best Attributes (significance level $\alpha = 0.05$)
 - Part of the Day
 - Pearson Correlation: 0.024
 - P-value: 0.00789
 - Elemental Fire Market Value
 - Pearson Correlation: -0.015
 - P-value: -0.0104
- Optimal Distance Metric
 - Cosine Distance (68% Accuracy)
 - All other distances around (58% Accuracy)
- Optimal Stopping Condition
 - Convergence of Centroids
 - Difference of 0.001

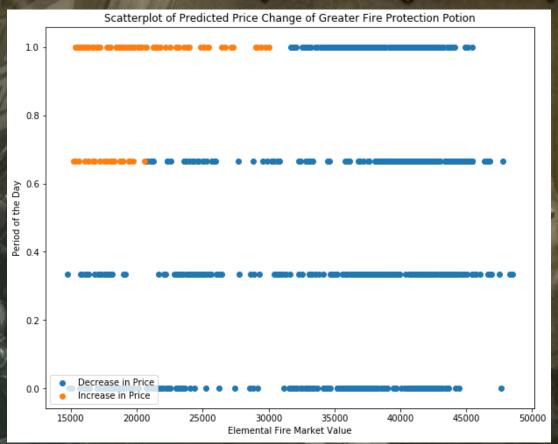


K-Means Clustering - Results



- Accuracy: 70.17%
- Confusion Matrix
 - 91% Bias towards Decreasing / No Change

	Decrease/ No Change	Increase
Decrease/ No Change	745	76
Increase	250	22



Conclusion

- Predicting price trends with Confidence Interval Estimation of worst/best performing time-intervals gave the best results.
 - Tuesday Afternoon is the best time to buy Greater Fire Protection Potion, while Wednesday Night is the best time to sell.
 - Correlates with weekly server reset and raiding schedules
- K-means cluster is the worst performing method of prediction for this situation
 - Only 70% accuracy
 - Too many variables and too much randomness in price to predict specific price changes